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An efficient method for human face recognition using nonsubsampled contourlet transform and support vector machine

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To improve the recognition rate in different conditions, a multiscale face recognition method based on nonsubsampled contourlet transform and support vector machine is proposed in this paper. Firstly, all face images are decomposed by using nonsubsampled contourlet transform. The contourlet coefficients of low frequency and high frequency in different scales and various angles will be obtained. Most significant information of faces is contained in coefficients, which is important for face recognition. Then, the combinations of coefficients are applied as study samples to the support vector machine classifiers. Finally, the decomposed coefficients of testing face image are used to test classifiers, then face recognition results are obtained. The experiments are performed on the YaleB database and the Cambridge University ORL database. The results indicate that the method proposed has performs better than the wavelet-based method. Compared with the wavelet-based method, the proposed method can make the best recognition rates increase by 2.85% for YaleB database and 1.87% for ORL database, respectively. Our method is also suitable for other face databases and appears to work well.

Keywords: multiscale geometric analysis, face recognition, nonsubsampled, contourlet, support vector machine.

1. Introduction

Now, biometric recognition is a topical issue. Especially, human face recognition has received a lot of attention for its wide applications in many fields, such as human identity authentication, building access control, human computer interface, surveillance and information retrieval, *etc*. Face recognition has been the subject of hotspot research [1–11].

There are some obstacles that make face recognition a very difficult task. The face images are usually acquired under different conditions. The image variations are mostly due to changes in the following parameters: age, disguise, pose, illumination, expression, facial hair, glasses/noglasses, and background, *etc*.

The different face recognition techniques have been proposed [1–3, 6, 7, 10, 11]. Three of the most classical methods for this purpose are principal component analysis (PCA), linear discriminant analysis (LDA) and independent component analysis (ICA). The well-known eigenface algorithm uses PCA for dimensionality reduction in order to obtain the best vectorized components that represent the faces. The vectors are projected to the basis vectors so that the projection coefficients are used as the feature representation of each face image [3]. ICA is very similar to PCA except that the distribution of the components is assumed to be non-Gaussian. The Fisherface algorithm derived from the Fisher linear discriminant analysis (FLDA) defines different classes with different statistics. Faces with similar statistics are grouped together by FLDA rules, where the difference between classes is maximized while the difference within classes is minimized. These methods may be less effective to handle the expression, illumination and pose problem.

Besides these methods, wavelet transform has been used in face feature extraction since it has the ability of localization in both frequency domain and time domain. The tremendous success of wavelet in other branches of image processing, inspired researchers to develop wavelet-based method for face recognition [1, 2, 4, 13–16]. Some experimental results have shown the superiority of the wavelet-based method with some of the existing popular algorithms: PCA, KPCA, LDA, ICA, *etc.* [1, 2, 4, 13, 16].

It is known that wavelets perform well at representing point singularities [16]. The usual orthogonal wavelet transform has wavelets with primarily vertical, primarily horizontal and primarily diagonal orientations. Unfortunately, this is not the case with higher dimensions because wavelets ignore the geometric properties of objects with edges and do not exploit the regularity of the edge curves.

Recently, a theory for high dimensional signals called multiscale geometric analysis (MGA) has been developed. Several MGA tools were proposed, such as curvelet [15, 16], bandelet [18] and contourlet [17–22] *etc*. In 2005, nonsubsampled contourlet was pioneered by Do and Zhou as the latest MGA tool [23–28]. These tools have better directional decomposition capabilities than wavelets. Especially, nonsubsampled contourlet transform is a “true” 2-D sparse representation for 2-D signals like images [18]. Thus nonsubsampled contourlet transform provides a better solution to approach curve features and extract biometric features.

YAN *et al.* [21] proposed a face recognition approach based on contourlet transform. It is promising since it achieved a 94% result on ORL database. HEDIEH SAJEDI *et al.* [22] presented an upright frontal face detection system based on contourlet transform and color images. Experimental results show that the algorithm proposed is effective and efficient in detecting frontal faces in color images. The detection rate is 93% and false positives (FP) rate is about 6%.

YANG *et al.* [23] proposed a multisensor image fusion method based on nonsubsampled contourlet transform. Extensive experimental results show that the proposed scheme performs better than the method based on the stationary wavelet transform [23].

ZHOU *et al*. [24] presented the nonsubsampled contourlet transform and its application in image enhancement. Experimental results show that the method proposed achieves better enhancement results than a wavelet-based image enhancement method [24]. CHAHIRA SERIEF *et al*. [28] proposed a new feature points extraction method based on the nonsubsampled contourlet transform for image registration. Preliminary experimental results show that the registration accuracy and robustness of the proposed algorithm are acceptable and very promising, and confirm the success of the NSCT-based feature points extraction approach [28].

In this paper, a face recognition method based on nonsubsampled contourlet transform and support vector machine (SVM) is proposed. The transform is used to extract face features. The SVM is used to determine the final face image classification.

The paper is organized as follows. Section 2 introduces the data preparation of face databases. Then, Section 3 describes nonsubsampled contourlet transform (NSCT). Section 4 gives out a detailed algorithm. Experimental results and simulations on YaleB and ORL databases are given in Section 5. The last section summarizes the paper and the conclusions are finally drawn.

2. Data preparation

To compare our face recognition method against the wavelet-based face recognition method, we tried our face recognition approach in two well-known databases.

2.1. YaleB database

The YaleB database contains 5760 single light source images of 10 persons, each seen under 576 viewing conditions (9 poses × 64 illumination conditions) [12]. For each person in a particular pose, an image with ambient (background) illumination was also captured. Hence, the total number of images is in fact 5760 + 90 = 5850. To facilitate visualization, we select a subset of 200 face images from the database with 20 images for each of ten persons. All images have been manually cropped and then normalized to a size of 192×168 with 256 gray levels.

2.2. Olivetti Research Laboratory (ORL) database

The Cambridge University ORL face database is composed of 400 images of ten different patterns for each of 40 persons [11]. The variations of the images are across time, size, pose and facial expression (open/closed eyes, smiling/not smiling). The 400 images from ORL database are used to evaluate the face recognition performance of NSCT- and SVM-based method.

3. Nonsubsampled contourlet transform

Contourlet is a new image representation scheme which owns a powerful ability to efficiently capture the smooth contours of images.

Contourlet transform can be divided into two main steps: Laplacian pyramid (LP) decomposing and directional filter banks (DFB). The original image is composed to a lowpass image and a bandpass image by LP decomposing. Each bandpass image is further decomposed by DFB. Repeating the same steps upon the lowpass image, the multiscale and multidirection decomposition of the image will be obtained [17−19, 21].

Due to downsamplers and upsamplers present in both LP and DFB, contourlet transform is not shift-invariant [16]. To achieve the shift-invariance, a nonsubsampled contourlet transform (NSCT) was proposed [23−28]. It is built upon nonsubsampled pyramids and nonsubsampled DFB. Thus, NSCT is a fully shift-invariant, multiscale, and multidirection image decomposition. It will be introduced below.

3.1. Nonsubsampled pyramid filter bank

The nonsubsampled pyramid filter bank (NSPFB or NSP) is different from PFB of the contourlet transform [17, 23]. The building block of NSPFB is a two channel nonsubsampled filter bank [23, 24]. A NSPFB has no downsampling or upsampling,

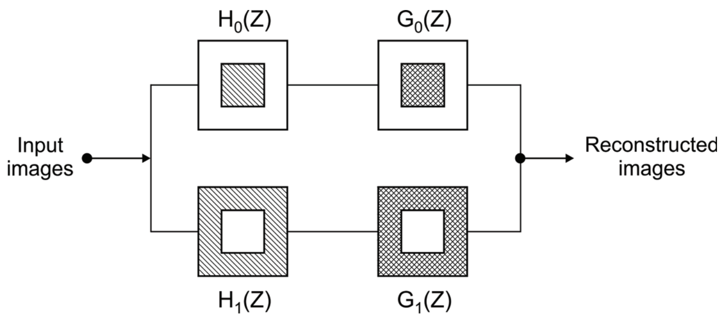

Fig. 1. Ideal frequency response of the building block.

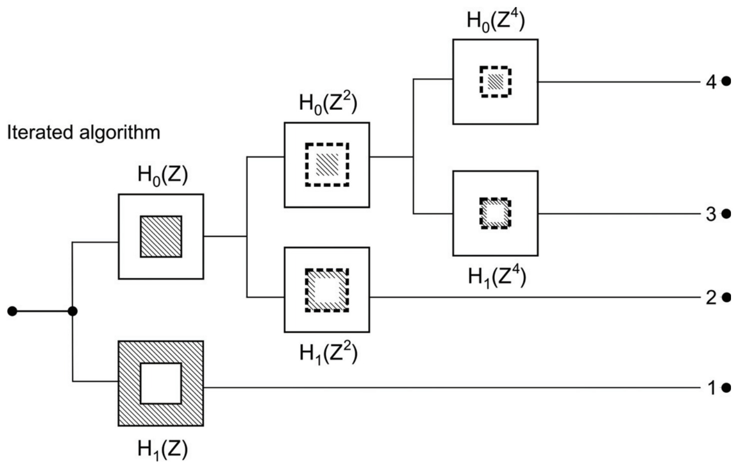

Fig. 2. Three-stage NSCT pyramid decomposition.

Hence, it is shift-invariant. The perfect reconstruction is achieved provided the filters satisfy the following identity

$$H_0(Z)G_0(Z) + H_1(Z)G_1(Z) = 1 \tag{1}$$

where $H_0(Z)$ is the lowpass decomposition filter, $H_1(Z)$ is the highpass decomposition filter, $G_0(Z)$ is the lowpass reconstruction filter, $G_1(Z)$ is the highpass reconstruction filter. An ideal frequency response of the building block of NSPFB is shown in Fig. 1.

In order to obtain the multiscale decomposition, NSPFB are constructed by iterated nonsubsampled filter banks [23, 28]. For the next level, all filters are upsampled by 2 in both dimensions. Therefore, they also satisfy the perfect reconstruction identity. Note that filtering with the upsampled filter $H(z^M)$ has the same complexity as filtering with using the *à trous* algorithm. The equivalent filters of a *t*-th level cascading NSPFB are given by

$$H_n^{es}(z) = \begin{cases} H_1\left(z^{2^{n-1}}\right)\prod_{j=0}^{n-2} H_0\left(z^{2^j}\right) & 1 \le n < 2^t \\ \prod_{j=0}^{n=1} H_0(z^{2j}) & n = 2^t \end{cases} \tag{2}$$

where z^j stands for $[z_1^j, z_2^j]$.

The cascading of the analysis part is shown in Fig. 2. Usually, we use maximally flat filters and 9-7 filters as NSPFB.

3.2. Nonsubsampled directional filter bank (NSDFB)

The nonsubsampled directional filter bank (NSDFB) is a shift-invariant version of the critically sampled DFB in the contourlet transform [24]. The building block of a nonsubsampled DFB is also a two channel nonsubsampled filter bank. In order to obtain finer directional decomposition, nonsubsampled DFB's are iterated. For the next level, all filters are upsampled by a quincunx matrix given by:

$$\mathrm{QM} = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$$

Then four-direction frequency divisions are obtained. The higher level decompositions follow a similar strategy [24–28].

Usually, we use diamond maxflat filters, ideal filters, ladder filters, orthogonal filters and regular linear phase biorthogonal filters as NSDFB.

3.3. Nonsubsampled contourlet transform (NSCT)

NSCT is constructed by combining NSPFB and NSDFB, as shown in Figure 3. The NSPFB provides multiscale decomposition and NSDFB provides directional

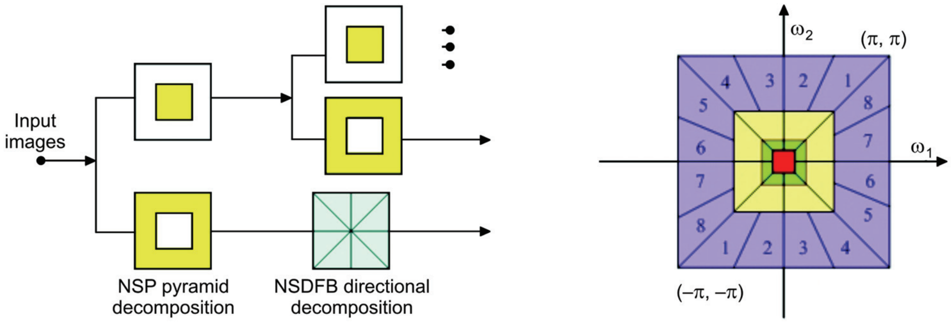

Fig. 3. Construction of NSCT: block diagram (**a**), resulting frequency division (**b**).

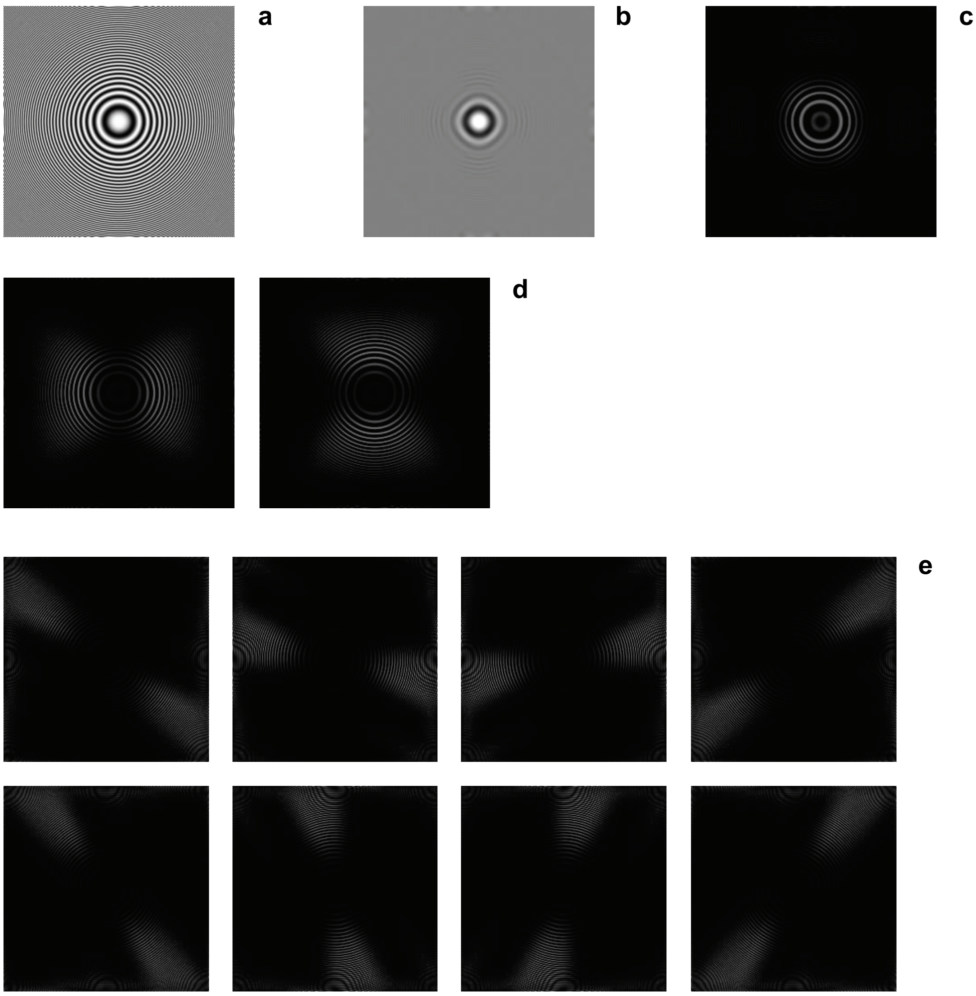

Fig. 4. NSCT demostration images: original image (**a**), NSCT coefficients – level 1 (**b**), NSCT coefficients – level 2 (**c**), NSCT coefficients – level 3 (**d**), NSCT coefficients – level 4 (**e**).

decomposition [23, 24]. This scheme can be iterated repeatedly on the lowpass subband outputs of NSPFB. First, a NSPFB splits the input into a lowpass subband and a highpass subband. Then, a NSDFB decomposes the highpass subband into several directional subbands. The scheme is iterated repeatedly on the lowpass subband.

Figure 4 shows the sample demonstration images by using NSCT: Fig. 4**a** shows an original image, and it includes low frequency and high frequency information; Figs. 4**b**–4**e** show the results of NSCT in different scales and different frequency division. We use four scales of decomposition for NSCT.

4. Algorithm description

4.1. Normalization

Let X_{face} and Y_{face} separately represent the training and testing face image sample sets. The size of all training and testing face images must be normalized to $k \times k$ pixels and gray level must be scaled to [0, 1].

4.2. Feature extraction and combination

In this stage, all training face images X_{face} are decomposed by using NSCT. As a result of performing NSCT, coefficients of low frequency and high frequency in different scales and various directions will be obtained. Denote the decomposed coefficients with same size $k \times k$ as C_1, $C_{2\text{-}1}$, $C_{2\text{-}2}$, ..., $C_{n\text{-}1}$, ..., $C_{n\text{-}v}$, where v is the number of directions. The coefficients contain most significant information of faces and are important for face recognition, so they can be called NSCT-faces.

Here, we use three scales of decomposition for NSCT. Then we use the coefficients of C_1, $C_{2\text{-}1}$ and $C_{2\text{-}2}$.

To reduce the computational cost and redundant information, the coefficients of $C_{2\text{-}1}$ and $C_{2\text{-}2}$ are combinated by using a muiltisensor image fusion method based on contrast vision model [29]. Then fused coefficients matrix C_2 with size $k \times k$ is obtained. So, the detailed information of the face images can be effectively preserved. The image fusion method based on contrast vision model performs better than other image fusion methods [29], and it is briefly introduced as follows.

Assume that block B_s is a small rectangle region. The block B_s in varying pixels is considered as an overlapped varying signal in a uniform background [29]. We define d_s, namely, a uniform parameter of partition block of coefficients C, as follows:

$$d_s = \frac{1}{m' \times n'} \sum_{(p,\, q) \in B_s} \frac{|C(p, q) - \mu_s|}{\mu_s} \tag{3}$$

where $m' \times n'$ is the block size, $C(p, q)$ is the coefficient in the p-th row and the q-th column, μ_s is the mean of block B_s. Here, we use a 5×5 block.

The fusion algorithm procedure consists of the following steps.

Step 1: Assume that there are two coefficient matrices of $C_{2\text{-}1}$ and $C_{2\text{-}2}$. The fusion algorithm decomposes both of them into smaller rectangle regions, *i.e.*, $m' \times n'$ blocks. $BC_{2\text{-}1\text{-}i}$ is the i-th block of $C_{2\text{-}1}$ and $BC_{2\text{-}2\text{-}i}$ is the i-th block of $C_{2\text{-}2}$.

Step 2: Calculate uniform parameters of blocks $BC_{2\text{-}1\text{-}i}$ and $BC_{2\text{-}2\text{-}i}$. Denote by $dC_{2\text{-}1\text{-}i}$ and $dC_{2\text{-}2\text{-}i}$ uniform parameters of the relative blocks $BC_{2\text{-}1\text{-}i}$ and $BC_{2\text{-}2\text{-}i}$.

Step 3: Compare the uniform parameters of two corresponding blocks $BC_{2\text{-}1\text{-}i}$ and $BC_{2\text{-}2\text{-}i}$, then construct block BC_i as:

$$BC_i = \begin{cases} BC_{2\text{-}1\text{-}i} & dC_{2\text{-}1\text{-}i} > dC_{2\text{-}2\text{-}i} \\ BC_{2\text{-}2\text{-}i} & dC_{2\text{-}1\text{-}i} \leq dC_{2\text{-}2\text{-}i} \end{cases} \tag{4}$$

Step 4: Repeat step 2 and step 3 on $m' \times n'$ blocks, the fused coefficients matrix C_2 will be constructed.

Combining the coefficients of C_1 and C_2, we obtain a coefficients matrix with size $2k \times k$. To reduce the computational cost of SVM classifier, we resize the coefficients matrix to a matrix with size $k/4 \times k/4$ by bilinear interpose algorithm. At last we reshape the matrix into a vector of $k^2/16$ elements.

4.3. Training SVM classifiers

The support vector machine (SVM) is used to determine the face image classification. SVM was first developed by Vapnik for pattern recognition and function regression [30]. It has also been proved to be very successful in many applications such as speaker recognition, iris recognition, face detection, object detection, palm classification, *etc*. SVM provides an efficient approach to the problem of classification by the kernel mapping technique. Using a kernel function, SVM is an alternative training method for polynomial, linear, Gaussian radial basis function, the exponential radial basis function, autocorrelation wavelet kernel and multilayer perceptron classifiers in which the weights of the network are found by solving a quadratic programming problem with linear constraints, rather than by solving a non-convex, unconstrained minimization problem as in standard neural network training [16, 30, 31].

Gaussian radial basis kernel has received significant attention from the machine learning community [14, 31]. The Gaussian radial basis function is defined as

$$K(x, x') = \exp\left[-\frac{\|x - x'\|^2}{2\sigma^2}\right] \tag{5}$$

where σ is the width of the Gaussian radial basis. Here, we use the Gaussian radial basis kernel.

For solving a multi-class problem, there are two most popular approaches: the one--against-all (OAA) method and the one-against-one (OAO) method [16, 30, 31]. For our purposes we use a OAA SVM because it constructs r binary classifiers as against $r(r-1)/2$ classifiers required for OAO SVM while addressing an r-class problem.

First, we construct r binary classifiers with Gaussian radial basis kernel. Then, we can apply the coefficients as study samples to the r binary classifiers.

4.4. Testing SVM classifiers

All testing face images Y_{face} must be decomposed by using NSCT. The coefficients must be combinated by using the multisensor image fusion method and reshaped into a vector of $k^2/16$ elements. We can apply the coefficients as testing samples to the r binary classifiers, then face recognition results will be obtained.

5. Experiments and results

All of the algorithms are implemented in MATLAB 7.3&C and executed on the same computer (Pentium E2140 1.6 GHz CPU, 2048 M RAM). All of the experiments are completed in the same environment. To compare our face recognition method against the wavelet-based face recognition method, the experiments are performed on the two face databases: YaleB database and ORL database. The original face images and NSCT-faces for two persons in YaleB face database are shown in Fig. 5.

Fig. 5. The original face images and NSCT-faces (level 1) for two persons in YaleB face database.

We select a subset of 200 face images from the YaleB database with 20 images for each of ten persons. 6 images for each of ten humans are used as training samples, and 14 images are used for testing samples. The face images under varying illumination and different pose are used in our experiments. The selected face images are very difficult to recognize. The division into training and testing set is random.

The original face images and NSCT-faces for two persons in ORL face database are shown in Fig. 6. We use all 400 images from the ORL database. 6 images for each of 40 humans are used as training samples, and 4 images are used for testing samples. The division into training and testing set is random.

Fig. 6. The original face images and NSCT-faces (level 1) for two persons in ORL face database.

A comparative study between the wavelet-based method and the NSCT-based method will be presented here. The results on YaleB database between the two schemes are shown in Tab. 1. The results on ORL database between the two schemes are shown in Tab. 2. We use three scales of decomposition for wavelet. Daubechies db2, db4, db6, db8 are used in wavelet-based method. We use three scales of decomposition for NSCT. The maximally flat filters and 9-7 filters are used as NSPFB. The diamond maxflat filters and ideal filters are used as NSDFB.

Especially, we can see from Tabs. 1 and 2 that the performance of our method is better than that of the wavelet-based method. Compared with the wavelet-based method, the method proposed can make the best recognition rates increase by 2.85% for YaleB database and 1.87% for ORL database, respectively.

In the experiments, σ (the width of Gaussian radial basis) has influenced the recognition rates. The relationships between the recognition rates and σ are shown in Figs. 7 and 8.

Table 1. Recognition rates for YaleB database.

			Recognition rates (different image size $k\times k$)		
		Filters	40×40	50×50	60×60
Methods	Wavelet-SVM	Daubechies 2	79.29%	84.29%	81.43%
		Daubechies 4	72.86%	72.14%	71.43%
		Daubechies 6	73.57%	76.43%	73.57%
		Daubechies 8	65.00%	67.14%	70.00%
	NSCT-SVM	Maximally flat filter + diamond maxflat filters	82.86%	85.00%	86.43%
		Maximally flat filter + ideal filters	81.43%	85.00%	86.43%
		9-7 filters + diamond maxflat filters	82.14%	85.00%	87.14%
		9-7 filters + ideal filters	81.43%	85.00%	87.14%

T a b l e 2. Recognition rates for ORL database.

Methods		Filters	Recognition rates (different image size $k \times k$) 40×40	50×50	60×60
Methods	Wavelet-SVM	Daubechies 2	93.75%	95.00%	93.13%
		Daubechies 4	95.63%	95.00%	93.13%
		Daubechies 6	91.87%	90.63%	91.25%
		Daubechies 8	95.00%	92.50%	89.38%
	NSCT-SVM	Maximally flat filter + diamond maxflat filters	96.88%	97.50%	96.88%
		Maximally flat filter + ideal filters	96.88%	97.50%	96.88%
		9-7 filters + diamond maxflat filters	96.88%	97.50%	96.88%
		9-7 filters + ideal filters	96.88%	97.50%	96.88%

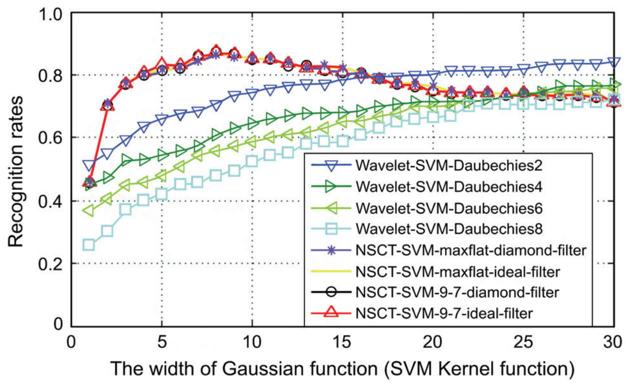

Fig. 7. Recognition rates for YaleB database.

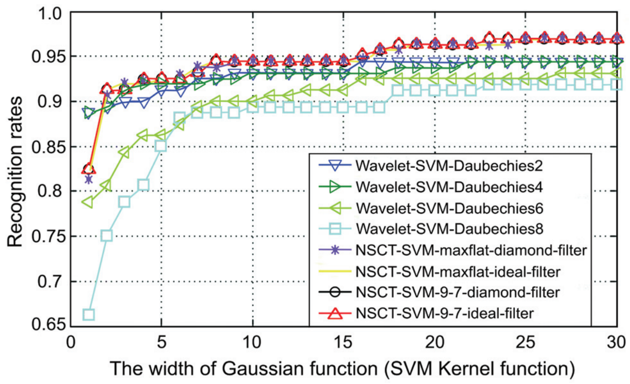

Fig. 8. Recognition rates for ORL database.

T a b l e 3. The results obtained using the PCA-based method and KPCA-based method.

Methods	Databases	The best recognition rates
PCA-SVM	YaleB database	53.57%
	ORL database	86.88%
KPCA-SVM	YaleB database	73.57%
	ORL Database	95.00%

T a b l e 4. Comparison of the computational cost using PCA, KPCA, wavelet and the method proposed.

	YaleB database			ORL database		
Methods	Training time [s]	Testing time [s]	Total time [s]	Training time [s]	Testing time [s]	Total time [s]
Wavelet(db8)-SVM	2.31	5.49	7.80	8.12	5.69	13.81
PCA-SVM	5.10	16.21	21.31	13.14	23.22	36.36
KPCA-SVM	4.23	14.96	19.19	11.96	19.93	31.89
NSCT-SVM	4.66	11.10	15.76	18.15	12.82	30.97

Table 3 shows the recognition rates using the classical PCA-based method and Kernel PCA-based method. Compared with the PCA-based method, the proposed method can make the best recognition rates increase by 33.57% for YaleB database and 10.62% for ORL database, respectively. Compared with the KPCA-based method, the proposed method can make the best recognition rates increase by 13.57% for YaleB database and 2.50% for ORL database, respectively.

Table 4 shows the computational cost using PCA-SVM, KPCA-SVM, wavelet--SVM and the method proposed. Daubechies db8 is used in wavelet-SVM method.

It can be noticed that the proposed method and wavelet-based method are practicable for large-scale datasets. They are the linear time algorithms (with the increment of the number of samples). The PCA-based and KPCA-based method are infeasible for large scale datasets because of the store and computational problem [32]. The Greedy KPCA and other modified methods can solve the problem [32, 33].

It is regreted that nonsubsampled contourlet transform has no fast algorithm. It is slower than wavelet transform. Although our method needs more recognition time, it obtains better accuracy than the wavelet-based method.

6. Conclusions

We can draw a number of conclusions from the research:

1. While the previous works mainly deal with subspace (or spatial domain), just like PCA, ICA, FDA and KPCA, we now pay more attention to the frequency domain and time domain. Their good performance appears to be due to two facts. One is that the lines and curves are the main features of facial images. It is experimentally confirmed that using NSCT to extract facial features is a more effective approach.

The other is that NSCT makes the proposed approach invariant to illumination and pose variations. Still, this is a robust and reliable face recognition technique.

2. Compared with the wavelet-based method, the proposed method can make the best recognition rates increase by 2.85% for YaleB database and 1.87% for ORL database, respectively. This method outperforms conventional wavelet-based method.

3. NSCT is a “true” 2-D sparse representation for 2-D signals like images. NSCT is more appropriate for the analysis of 2-D signals which have line, curve or hyper-plane singularity than wavelet, and it has better approximation precision and sparsity description. NSCT transform allows for different and flexible number of directions at each scale, and NSCT can efficiently capture the intrinsic geometrical structures in natural images such as smooth contour edges and is fully shift-invariant.

4. In this paper, we combine the idea of NSCT and the multisensor image fusion method to reduce the computational cost and redundant information. The image fusion method based on contrast vision model can effectively preserve the detailed information of the source face images. Therefore, the method proposed provides satisfactory recognition results.

In conclusion, the NSCT-based method is a novel attempt to apply NSCT to pattern recognition and can also be applied to other biometric recognition problems, such as iris recognition, fingerprint recognition, palmprint recognition and multimodal biometric recognition, *etc*.

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